

Historic Trends in U. S. Drought Forcing in a Warming Climate

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Abstract

The mean North American and world climates have warmed since the beginning of climatologically significant anthropogenic emission of greenhouse gases in the 19th Century. It has been suggested that warming may increase the frequency or severity of droughts. We define and study the statistics of an aridity index that describes the precipitation forcing function of drought, considering drought to be a season with low enough precipitation to be significant for agriculture. Our aridity index is a reciprocal function of the seasonal precipitation, which is more significant for agriculture than mean precipitation. Using NOAA data from sites in 13 diverse climate regimes in the 48 contiguous United States with time series running over the period 1940–1999 but including two data series from 1900 or 1910, and computing their decadal averages, we search for linear trends in their aridity indices. We find no linear trends significant at the 2σ level. At five sites 3σ upper bounds on any systematic trends are in the range 1.0–2.8%/decade, while at two sites 3σ lower bounds are -0.5%/decade and -2.2%/decade; at other sites the bounds are less restrictive.

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I. INTRODUCTION

The mean world climate has warmed [1–5] since the the beginning of climatologically significant anthropogenic emission of greenhouse gases in the 19th Century. It has been suggested [6–8] that warming is accompanied by increases in the frequency of “extreme weather events”, a broad category that includes severe storms and drought. Conclusions drawn from single extreme events are controversial[9], but long term averages carry more statistical power.

There are many ways of defining “extreme events”, and it is necessary to find objective quantitative measures. It is difficult to predict future changes in the hydrological cycle from climate models [10], but guidance may be found in the historic record of climate as it has warmed over the last century. In this paper we are concerned with the periods of low precipitation that are the forcing function of drought.

Drought has been a concern of humanity since the prehistoric development of agriculture. It is a complex phenomenon that may be defined in many ways. For example, the widely used Palmer Drought Index (PDI) and the Palmer Drought Severity Index (PDSI) [11–14] involve a complex interplay among precipitation and modeled evapotranspiration, soil moisture, runoff and recharge (but do not include the effects of humidity, vegetation, cloud cover, precipitation rate, wind and soil permeability). The PDI and PDSI are useful to agriculturalists and water resource engineers because they measure the deviation of local conditions from their long-term means that are the basis of planting and planning. These indices filter the precipitation forcing through a complex and model-dependent transfer function. To consider the possible effects of climate change on drought we separate the forcing by precipitation from other processes, even while acknowledging that these other processes (such as temperature change, which affects the evapotranspiration rate) contribute to the response of the hydrological system.

A number of other drought indices exist [14, 15], but are also imperfect tools for studying the possible effects of climate change on precipitation. For example, the Standardized Precipitation Index (SPI) [16–19] compares the precipitation at a site over some period (chosen in the range from one month to several years) to the statistical distribution of recorded precipitation at that site in periods of that length. This identifies anomalous (unusually dry or wet) periods that are then assigned a quantitative index value based on the fraction of

such periods in the record that were dryer or wetter. The SPI describes how unusual is the value of precipitation at that site (without making the unproven assumption of a Gaussian distribution), rather than quantifying the magnitude of its deviation from the mean or its implications.

Many previous studies of long term precipitation trends have been concerned with total annual precipitation. This is a measure of climate change that is not directly applicable to drought; a dearth of precipitation over a few months of a growing season is drought to the farmer, even if the annual total is high.

Studies of drought trends using the Palmer Drought Severity Index (PDSI; [13, 20–22]) are inconsistent, with the earliest work finding no evidence of a trend but some recent work [14, 23] indicating a drying trend during a period that mostly overlaps with that considered here. Because the PDSI includes soil drying as a result of increased evapotranspiration as the climate warms, it conflates effects of precipitation and temperature changes [24] and is not a direct measure of the precipitation forcing function. Warming increases evapotranspiration and biases the PDSI towards drought. Our purpose is to determine or constrain directly any historic trend in the precipitation forcing function.

Longer term studies [14, 25] suggest a correlation between proxy drought measurements in North America and the (northern European) Medieval Warm Period. Their applicability to the modern period of warming by greenhouse gases is uncertain.

Studies using the SPI may be more directly comparable to ours, but are few. For example, [26] modeled drought in the northeastern United States and [27] analysed SPI data for Hungary, but neither of these publications present detail sufficient for comparison.

The purpose of this work is to determine if extended periods of low precipitation that are the forcing function of droughts have become more (or less) frequent or severe in the 48 contiguous United States as the climate has warmed in the last century. We wish to separate changes in precipitation from those of temperature with which they are conflated in drought indices. Dearth of precipitation are basic and elemental parameters of climate change. We ask if the frequency and severity of periods of low precipitation have changed. This question has comparatively simple and unambiguous statistical measures, free of the complications, inherent in drought indices, of including parameters, such as humidity, vegetation, cloud cover, precipitation rates and wind, for which data may be absent or limited, but that affect evapotranspiration and runoff.

In order to avoid the subtleties and complications of modeling [23] our approach is entirely empirical, and we forgo any attempt to interpret these historical results as tests of the validity of climate models or of their predictions of drought. Nor do we attempt to separate secular or very long term (on time scales of 50 years or more) trends from natural variability on shorter time scales. Because of the “red” spectrum of natural climatic variation [28, 29] and its complex dependence on space, time and the variable considered [30], we do not attempt the difficult task [31] of separating long term natural variations from gradual anthropogenic climate change.

Here we define an empirical aridity index that measures any seasonal dearth of precipitation, compute its decadal averages, and determine or bound any long term trends. We consider 13 sites in distinct climatic zones within the 48 contiguous United States, with data records from 1940–1999 for most sites, but with two extending back to the first decade of the 20th Century. Because drought conditions are generally regional, these comparatively few sites sample the climate of a large area, including most North American climate zones. From these data we are able to bound the historic rate of change of the precipitation forcing function of drought.

II. METHODS

We use a NOAA hourly precipitation database [32] to construct precipitation totals $P_{i,j}$ for the three-month periods, approximately corresponding to the seasons, January–March, April–June, July–September and October–December, where i denotes the site and j the calendar quarter and year. We define the annual mean seasonal aridity index:

$$A_{i,Y} \equiv \frac{1}{4} \sum_{j \in Y} \frac{1}{(P_{i,j} + C)^2}, \quad (1)$$

where Y denotes the year. This index is strongly influenced by the severity of dry periods, and much less by variations in precipitation in wet periods. This metric differs from the frequently used [14, 23] mean annual precipitation; the agriculturalist is chiefly concerned with dry seasons that are hardly mitigated by intervening wet periods.

$A_{i,Y}$ is regularized by the addition of the constant C to the denominator, avoiding a singularity if there is no precipitation at all. We take $C = 6'' = 15.24 \text{ cm}$ so that agriculturally insignificant precipitation has little effect on a quarter’s contribution to $A_{i,Y}$. In order to

avoid bias resulting from the omission of a season (that might be seasonally dry or wet) when only incomplete data are available, $A_{i,Y}$ is not computed if precipitation data are not available for the entire year, and that year is excluded from the analysis.

We define the decadal averaged mean seasonal aridity index:

$$A_{i,D} \equiv \frac{1}{N_{i,D}} \sum_{Y \in D} A_{i,Y}, \quad (2)$$

where $N_{i,D}$ is the number of years with complete data in the decade D . If fewer than five years are present $A_{i,D}$ is not computed. The uncertainty of $A_{i,D}$ is estimated:

$$\sigma_{i,D} \equiv \frac{1}{N_{i,D}} \sqrt{\sum_{Y \in D} (A_{i,Y} - A_{i,D})^2}. \quad (3)$$

III. RESULTS

The $A_{i,D}$, with error bars $\pm\sigma_{i,D}$, are plotted in Fig. 1. Specifications of the sites, χ^2 of the no-trend (null) hypothesis and parameters of the best fit linear trends are shown in Table I.

As expected, the aridity index is largest at the desert site 2 (its maximum possible value is $(6'')^{-2} = 0.0278''^{-2}$), and almost as large at Californian sites 8 and 13 where summer precipitation is rare. Next largest are high Plains sites 6 and 1, and then more easterly sites with more summer precipitation. Finally, the aridity index has its lowest values at site 7 on the Olympic peninsula, with year-round frequent light precipitation.

We find no linear trends significant at the 2σ level. At five sites the 3σ upper bounds on any such trends are in the range 1.0–2.8%/decade, while at two sites the 3σ lower bounds are -0.5%/decade and -2.2%/decade; at other sites the bounds are less restrictive. This result is consistent with the prediction [33] that a 1.4°C warming, nearly twice the warming since the beginning of the industrial era (and an even greater multiple of the warming over the span of our data), will be required for precipitation changes to become statistically significant (*N.B.*: These authors are concerned with wet season precipitation, while our aridity index measures the driest seasons of the year, so these results, though consistent, are not strictly comparable.).

Our uncertainty estimates assume a normal distribution. While it is known (and obvious) that short-term precipitation statistics are far from Gaussian, these estimates only assume

Key	NOAA Site	Location	Lat. (N)	Long. (W)	χ^2 (d.o.f.)	Slope
1	140620	Bazine 13 mi SSW, KS	38° 16'	99° 45'	1.49 (4)	-1.4 ± 2.2
2	020080	Ajo, AZ	32° 22'	112° 52'	1.17 (4)	-1.1 ± 1.3
3	366889	Philadelphia Airport, PA	39° 52'	75° 14'	19.80 (9)	$+1.0 \pm 0.5$
4	010008	Abbeville, AL	31° 25'	85° 17'	8.39 (3)	-5.5 ± 3.2
5	081271	Canal Point Gate 5, FL	26° 52'	80° 38'	4.35 (4)	$+3.9 \pm 2.7$
6	241088	Bredette, MT	48° 33'	105° 16'	10.40 (5)	-1.2 ± 0.8
7	450013	Aberdeen 20 mi NNE, WA	47° 16'	123° 42'	0.37 (4)	$+0.3 \pm 4.9$
8	047633	Sacramento, CA	38° 25'	121° 30'	5.50 (5)	$+0.5 \pm 1.0$
9	310301	Asheville, NC	35° 35'	82° 33'	17.42 (8)	-1.1 ± 0.7
10	111577	Chicago Midway Airport, IL	41° 44'	87° 47'	6.61 (4)	-3.8 ± 2.0
11	217294	St. Cloud, MN	45° 33'	94° 03'	4.34 (4)	$+2.0 \pm 2.1$
12	431081	Burlington, VT	44° 28'	73° 09'	30.03 (4)	$+2.0 \pm 1.4$
13	045114	Los Angeles Int. Airport, CA	33° 56'	118° 24'	0.46 (4)	-0.5 ± 1.4

TABLE I: Sites and results. The penultimate column gives χ^2 and (number of degrees of freedom) for the hypothesis of a constant aridity index $A_{i,D}$ equal to its uncertainty-weighted mean. The last column gives the best fit linear trend of $A_{i,D}$ and its $\pm 1\sigma$ uncertainty in %/decade.

that the distribution of annual values within a decade of the aridity index is Gaussian, a plausible (though unproven) assumption because many weather systems contribute to a seasonal or annual precipitation total. Because of the existence of long-time correlations (“red” noise) in geophysical data [28, 29], it is likely that the tails of the distributions are greater (“fatter”) than those of normal distributions. If we had found apparently significant trends, this would reduce their statistical significance; here it weakens (to a degree that cannot be calculated because we do not know the true distributions) the bounds that can be placed on trends. It does not weaken our null result that no significant trends can be found in the data.

Despite the absence of significant linear trends, the constant hypothesis is rejected by the χ^2 test at the $P < 0.02$ level at site 3, at the $P < 0.03$ level at site 9, and at the $P < 0.001$ level at site 12. This reflects the well-known fact that there are long-period (decadal and

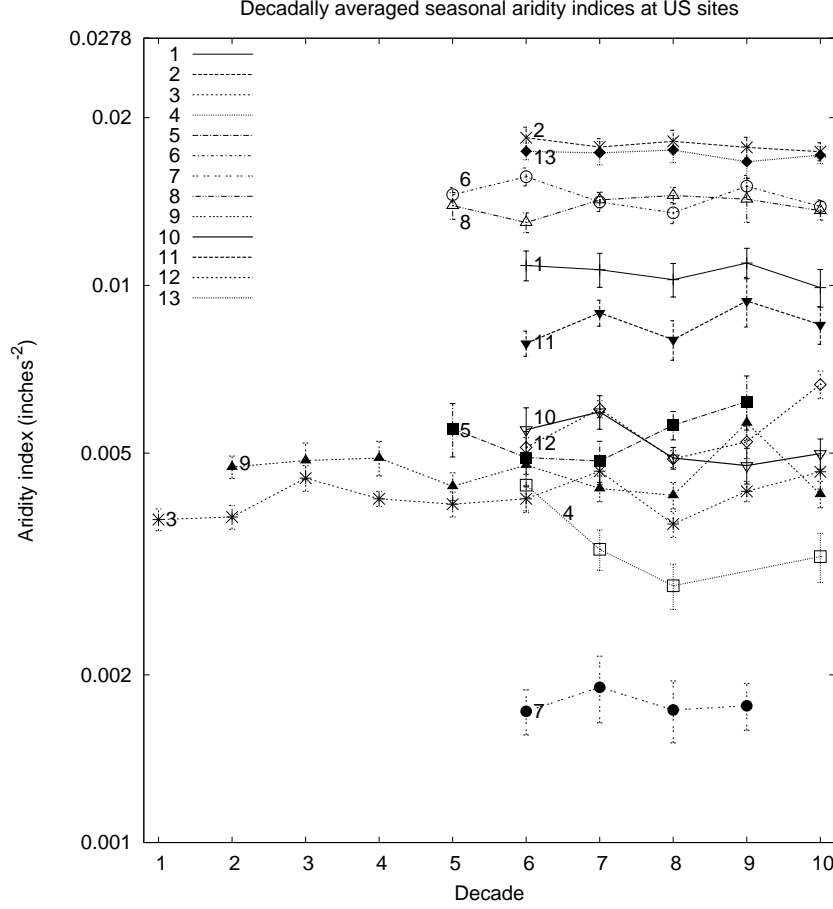


FIG. 1: Aridity indices $A_{i,D}$ at 13 sites in the 48 contiguous United States. Error bars are $\pm 1\sigma$. Decade 1 is 1900–09, *etc.* The maximum possible value of $A_{i,D}$ is $0.0278/\text{in}^2$.

longer) variations in the climate system [28, 29, 34–36], so that decadal means may differ significantly from longer-term means even in the absence of a linear trend.

Appendix A: Data

We use precipitation data from [32], summing the rainfall in each quarter. When hourly data are missing we use the cumulative data. We searched the data for anomalous values, such as negative values or values in excess of $5''$ in one hour. Such large values might indicate suspect data because the all-time record hourly rainfall in the 48 contiguous United States is $8''$, and most state all-time hourly records are in the range 5 – $7''$ [37]. We found only one such instance in our database, an hourly value of more than $10''$ that was inconsistent with

the daily total of less than 2'' and that we discarded, using the daily value.

Data were included from years for which the data sets were complete. These years are indicated in Fig. 2. Decadal means and standard deviations (obtained from the standard deviations of the aridity indices for that site within the decade considered) were computed only if data were available for at least five years in the decade; other decades were omitted.

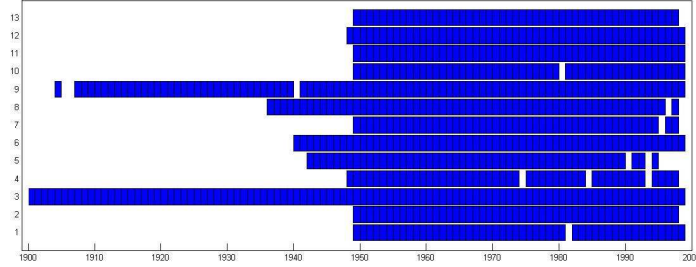


FIG. 2: Data coverage, showing years with complete data at our 13 sites. Decadal averages are only computed if there are five or more years of data in the decade.

In order to check for data homogeneity, we calculated the run statistics [38] of deviations from their means of the annual aridity index for each site and from the linear fits to these annual data; these two statistics gave essentially identical results. We found no statistically significant deviations from homogeneity at twelve of our sites, but at site 12, where the constant hypothesis is rejected at the $P < 0.001$ level by the χ^2 test, inhomogeneity was significant at the 98% confidence level. These results are not independent; they reflect roughly decadal variations that appear both as significant deviations of decadal means from a constant value and as long runs of positive or negative annual deviations from the mean (and hence fewer distinct runs than for homogeneous data), despite the absence of a significant linear trend. This result may be interpreted as the consequence of natural variability, as was found for Scottish rainfall [39]. However, finding one such result in 13 independent data series is only significant at the 75% level.

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